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ECONOMETRIC MODELS and ECONOMIC FORECASTS

FOURTH EDITION

Robert S. Pindyck
Daniel L. Rubinfeld

ECONOMETRIC MODELS AND ECONOMIC FORECASTS

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reader should check, using the above procedure, that the estimator $\Sigma y_i z_i / \Sigma z_i^2$ does not yield a consistent estimator of β (see Exercise 7.2).

The technique of instrumental variables appears to provide a simple solution to a difficult problem. We have defined an estimation technique which yields consistent estimates if we can find an appropriate instrument. However, this is likely to be difficult when errors of measurement are present.

A few concluding comments may be instructive. First, the ordinary least-squares estimation technique is actually a special case of instrumental variables. This follows because in the classical regression model X is uncorrelated with the error term and because X is perfectly correlated with itself. Second, if we generalize the measurement-error problem to errors in more than one independent variable, one instrument is needed to replace *each* of the designated independent variables. Finally, we repeat that instrumental-variables estimation guarantees consistent estimation but does not guarantee unbiased estimation.

7.3 SPECIFICATION ERROR

Our discussion of econometrics has relied heavily on the assumption that the model to be estimated is correctly specified. Once the correct specification of the model is assumed, model estimation and model testing become relatively straightforward. In reality, however, we can never be sure that a given model is correctly specified. In fact, researchers usually examine more than one possible specification, attempting to find the specification which best describes the process under study. We attempt to give the reader a feeling for the hazards involved in searching for a model by discussing the costs associated with model misspecification. We concern ourselves with two types of misspecification, the first occurring when relevant variables are omitted from the linear regression and the second occurring when irrelevant variables are added to the equation. Finally, we pause briefly to discuss misspecifications associated with the incorrect choice of functional form.

7.3.1 Omitted Variables

Consider first the case in which a variable is unknowingly omitted from a "true" or correct model specification. Assume that the true model is given by Eq. (7.7),

$$y_i = \beta_2 x_{2i} + \beta_3 x_{3i} + \varepsilon_i \quad (7.7)$$

while the regression model is given by³

$$y_i = \beta_2^* x_{2i} + \varepsilon_i^* \quad (7.8)$$

³ We will work with data in deviations form and assume that $\bar{e} = 0$ to simplify the derivations. Most, but not all, of the results hold for the intercept of the equation. Since the effect of model misspecifications on the intercept usually is not of paramount importance, we leave the details to the reader (see Exercise 7.3).